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Active vibration suppression of a composite I-beam using fuzzy positive position control

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Abstract
Positive position feedback (PPF) control is widely used in active vibration control of flexible structures. To ensure quick vibration suppression, a large PPF scalar gain is often applied. However, PPF control with a large scalar gain causes initial overshoot, which is undesirable in many situations. In this paper, a fuzzy gain tuner is proposed to tune the gain in the positive position feedback control to reduce the initial overshoot while still maintaining quick vibration suppression. The fuzzy system is trained by a batch least squares algorithm based on desired input–output data so that the trained fuzzy system can behave like the training data. A 3.35 m long composite I-beam with piezoceramic patch sensors and actuators is used to demonstrate the fuzzy PPF control. For comparison purposes, three types of control methods are used in the experiment: a standard PPF control, a standard PPF control with traditional fuzzy gain tuning, and a PPF control with batch least squares fuzzy gain tuning. Experimental results clearly demonstrate that PPF control with batch least squares fuzzy gain tuning behaves much better than the other two control methods in terms of successfully reducing the initial overshoot and quickly suppressing vibration.

(Some figures in this article are in colour only in the electronic version)

1. Introduction

For structural vibration control, positive position feedback (PPF) control was first proposed by Goh and Caughey in 1985 [1]. The PPF control is applied by feeding the structural position coordinate directly to the compensator and then the product of the output from the compensator and scalar gain is positively fed back to the structure. To ensure that a vibration is quickly suppressed, a large scalar gain is often used in a PPF controller. However, PPF control with a large gain causes initial overshoot [2], which is undesirable in many situations. An effective way to reduce the initial overshoot is to tune the PPF scalar gain. There are many ways of tuning the gain, but most of the methods have discrete outputs and abrupt gain changes. Fuzzy logic was introduced by Zadeh [3] in 1965 to give a possible mathematical representation of vagueness and approximation in a continuous fashion.

As an alternative to the classical control theory, fuzzy logic control deals with the uncertainty factors and does not require a precise mathematical model. Moreover, it has been used in the field of active vibration control. Casciati *et al* [4] proposed a fuzzy chip for nonlinear vibration control to solve the problem of slow reaction time for a software-implemented controller. Takawa *et al* [5] designed a fuzzy controller for vibration suppression of a composite beam. The fuzzy controller is based on the fuzzy model by using modern control theory. Shen *et al* [6] proposed fuzzy proportional, integral plus derivative (PID) control for vibration control of flexible structures. Yoshimura *et al* [7] presented an active suspension system for passenger cars, using linear and fuzzy logic controllers. Kwak and Sciulli [8] proposed

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Figure 1. The experimental set-up.

a state-space fuzzy rule for the vibration suppression of a cantilever beam with surface-bonded piezoceramic sensors and actuators. Experimental results show the successful vibration suppression by the fuzzy rule. Fuzzy vibration control can be further extended to suppress vibrations of systems with uncertainties. Zeinoun and Khorrami [9] proposed a fuzzy adaptive controller for active vibration suppression on a clamp-free beam instrumented with piezoceramic sensors and actuators. The experimental results demonstrate the robustness of the proposed controller by introducing large parameter perturbations during the experiment. Mayhan and Washington [10] proposed a fuzzy model reference learning controller to dampen the fundamental vibration mode of the cantilever beam system with piezoceramic actuators and sensors. The robustness of the fuzzy model reference controller is shown by adding extra masses to the beam. Fuzzy active vibration control can be applied to a multi-input/multi-output (MIMO) system. Huang and Lian [11] developed an MIMO hybrid fuzzy controller for a lumped mass system. This fuzzy system consists of a conventional fuzzy controller for the main dynamic performance of the system and a decoupling fuzzy controller for the compensation of the dynamic coupling effect of the system. Experimental results show that the system is effective in suppressing vibration. Combined with an artificial neural network (ANN), a fuzzy system has learning ability. Wang and Frayman [12] proposed a dynamically generated fuzzy neural network (DGFNN) which can be used for torsional vibration control of tandem cold-rolling mill spindles with a minimal knowledge of the system. The DGFNN is capable of expressing the knowledge acquired from input–output data in terms of fuzzy inference rules. Compared with conventional methods, the DGFNN gives the best results for reducing the speed deviation and suppressing the torsional vibration of the spindles. The optimization of the parameter of the fuzzy controller is an important issue in fuzzy active vibration control. Lu *et al* [13] utilized a genetic algorithm to optimize the membership functions of a fuzzy logic controller for vibration control purposes. According to the vibration characteristics, a new encoding method and a fitness function with variable factors are presented to evaluate the performance. The effectiveness of the genetic-algorithm-based fuzzy controller is demonstrated with a cantilever beam with piezoelectric materials attached.

In this paper, a fuzzy gain tuner is proposed to continuously tune the scalar gain in a positive position feedback control system. A desired input–output data set is used to train the fuzzy system by the batch least squares algorithm. The object for the experiment is a 3.35 m long composite I-beam in a cantilevered position with surface-bonded piezoceramic patches. For comparison purposes, three types of control methods are used in the experiment: a standard PPF control, a standard PPF control with traditional fuzzy gain tuning, and a PPF control with batch least squares fuzzy gain tuning. In the experiments, the PPF control with batch least squares fuzzy gain tuner performs much better than the standard PPF control and the traditional fuzzy gain tuning PPF control. Experimental results reveal that the vibrations are quickly suppressed with reduced initial overshoot when the batch least squares fuzzy gain tuning PPF control is implemented.

Table 1. I-beam properties.

Quality	Description	Units	Value
L	Beam length	m	3.35
w_b	Beam width	mm	100
h_b	Beam height	mm	102
t_b	Beam thickness	mm	6
ρ_b	Beam density	kg m^{-3}	1850

2. Experimental set-up and open loop testing

The experiment is implemented on a pultruded fiber-reinforced polymer (FRP) composite thin walled I-beam using smart sensors and actuators. The experimental set-up is shown in figure 1. The FRP I-beam is made of E-glass fibers and polyester resins. The properties of the I-beam are shown in table 1. PZT (lead zirconate titanate) type piezoelectric ceramic patches are used as smart sensors and actuators. The 3.35 m long beam is cantilevered at one end and PZT patches are surface-bonded to it. Two PZT patches are bonded on the top and bottom flange surfaces respectively, and these two patches are used as actuators to excite and to enable active vibration control of the beam. One PZT patch is bonded on the top flange of the beam, that acts as sensor for the feedback of the signals in the active control algorithms. The properties of the PZT patches are shown in table 2.

The vibration suppression algorithm is implemented in Matlab/Simulink and then downloaded to the dSPACE digital data acquisition and real-time control system for implementation. The dSPACE system has an analog to digital converter and a digital to analog converter. The dSPACE ControlDesk module is used to develop a graphical user

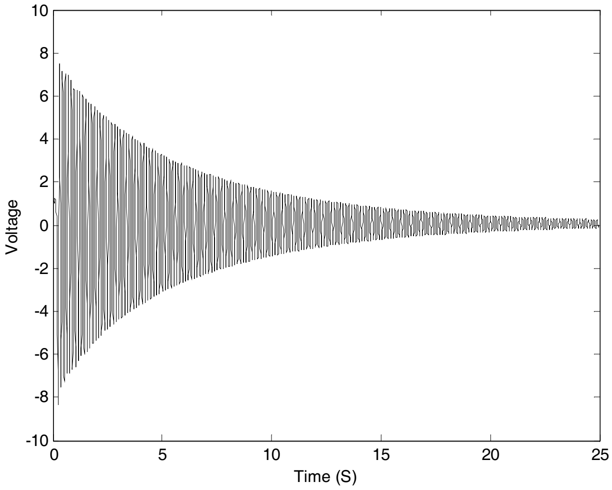

Figure 2. Time response of the open loop testing.

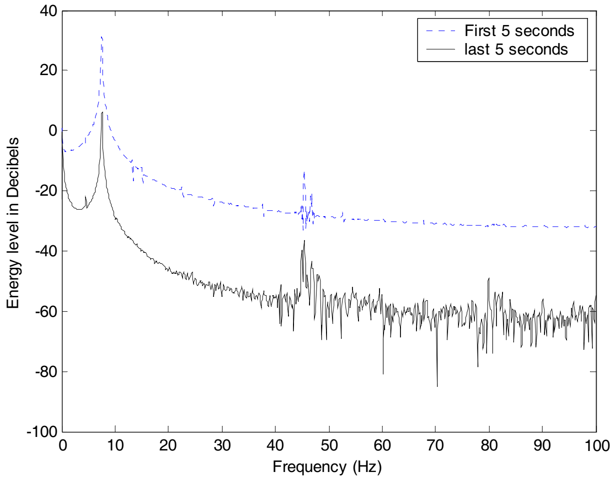

Figure 3. Power spectrum density plot of the open loop testing.

interface (GUI) for online parameter adjustment and real time data acquisition.

Open loop testing was conducted by manually impacting the FRP I-beam with multimodal excitation. The time response of open loop testing in the first 25 s period is shown in figure 2. Data of open loop testing are then fast Fourier transformed (FFT) to generate power spectrum density (PSD) plots for the first 5 s and last 5 s, as shown in figure 3. PSD plots describe the distribution of the power contained in a signal over a certain frequency range. From the comparison of these two PSD plots, it can be seen that the 7.4 Hz is the dominant mode since it has the highest power peak value in both the first 5 s and last 5 s while the power of other modes dramatically attenuates in the latter stage.

To achieve satisfactory active vibration suppression, the dominant mode (7.4 Hz) of the FRP I-beam should be the target frequency for the control design. For a fair comparison of different controls, a computerized excitation will be used to induce vibration of the I-beam. The excitation signal is a combination of a sinusoidal wave at the first modal frequency and a white noise. In all experiments, the excitation lasts for

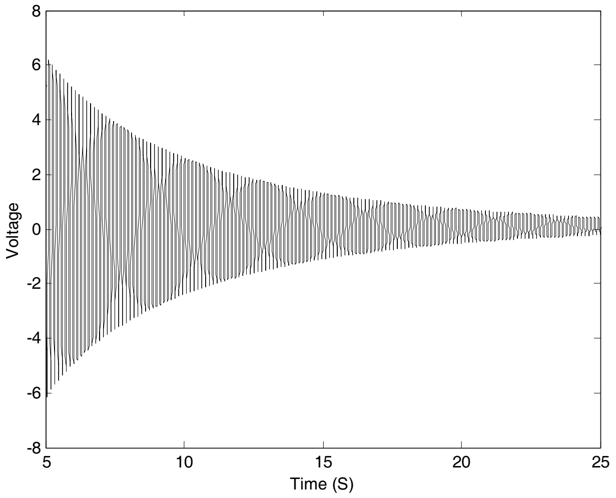

Figure 4. Time response of the free vibration.

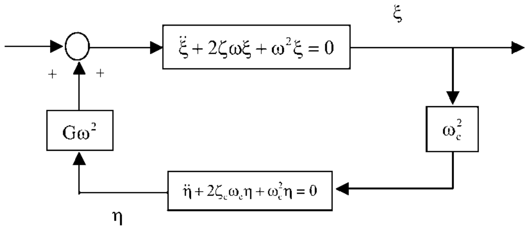

Figure 5. Block diagram of the PPF controller.

5 s. Figure 4 shows the response of the beam after such an excitation without any control. Please note that the time in this figure starts at the end of the fifth second.

3. Standard positive position feedback (PPF) control

One advantage of positive position feedback (PPF) control is that its frequency response rolls off quickly, making the closed loop system robust to spillover [14]. The block diagram of the PPF controller is shown in figure 5. In PPF control, structural position information is fed to a compensator. The output of the compensator, multiplied by a scalar gain, is fed directly back to the structure. The equations describing PPF control are given as

$$\text{Structure: } \ddot{\xi} + 2\zeta\omega\xi + \omega^2\xi = G\omega^2\eta \tag{1}$$

$$\text{Compensator: } \ddot{\eta} + 2\zeta_c\omega_c\eta + \omega_c^2\eta = \omega_c^2\xi \tag{2}$$

where ξ is a modal coordinate describing displacement of the structure, ζ is the damping ratio of the structure, ω is the natural frequency of the structure, G is the scalar feedback gain, η is the compensator coordinate, ζ_c is the compensator damping ratio and ω_c is the frequency of the compensator.

The compensator is composed of a second-order filter with the same form as that in the modal equation (1), but with a much higher damping ratio. To achieve maximum damping, ω_c should be closely matched with ω. Also a structure with the modal frequency above ω_c will experience increased stiffness

Table 2. Properties of PZT patches used on the beam.

Quality	Description	Units	PZT actuator	PZT sensor
$l \times w \times t$	Dimensions	cm	$10.16 \times 3.81 \times 0.08$	$5.08 \times 3.81 \times 0.038$
d_{33}	Lateral strain coefficient	$\mathrm{C\,N^{-1}}$	550×10^{-12}	350×10^{-12}
K_3^T	Dielectric constant		3250	1800
ρ_P	PZT density	$\mathrm{kg\,m^{-3}}$	7700	7700
E_P	Young's modulus	$\mathrm{N\,m^{-2}}$	6.9×10^{10}	6.9×10^{10}

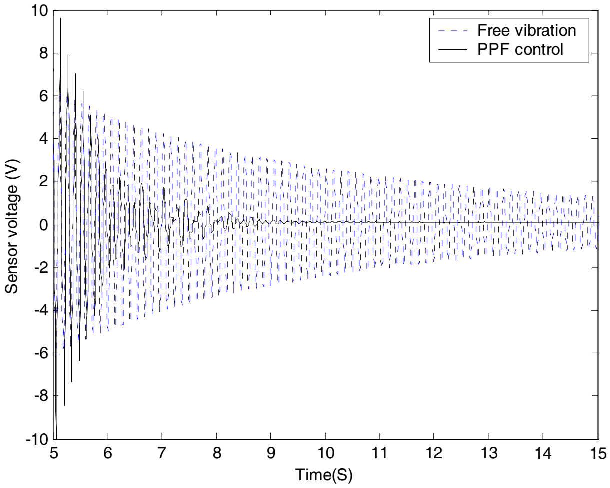

Figure 6. Comparison of free vibration and PPF control.

with the PPF control. This often results in high structural modes being excited by the PPF control [2, 15].

The target frequency of the standard PPF control is the first mode frequency (7.4 Hz) of the composite I-beam. The beam is excited by the signal, as described in section 2, for the initial 5 s. After the initial 5 s, the excitation is stopped and the standard positive position feedback control is implemented on the composite I-beam to suppress the vibration. The comparison of the time responses of free vibration and standard PPF is shown in figure 6. With the PPF control, the vibration is successfully suppressed in five seconds. However, the PPF control result is not good enough, since there is an initial overshoot, which may cause damage to the system. So there is a need to use the fuzzy gain tuning method to depress the initial overshoot of PPF control.

4. Fuzzy gain tuning of PPF control of the beam

This section presents two fuzzy methods, namely the traditional fuzzy method and the batch least square fuzzy method, to tune the scalar gain in a PPF controller to eliminate the initial overshoot while achieving quick vibration suppression.

4.1. Design procedure of gain tuner using traditional fuzzy logic method

The following briefly describes the design procedure of the traditional fuzzy system to tune the scalar gain in a PPF controller.

(1) *Choose the appropriate input and output variables for the gain tuner.* The absolute value of sensor voltage which is proportional to the vibration amplitude is chosen as the input variable. The PPF scalar gain is chosen as the output variable.

(2) *Define the linguistic variables to form a database.* Four linguistic variables (small, less medium, medium, large) are used to represents the input domain and output domain with their membership values lying between 0 and 1. If the number of linguistic variables is chosen too big it will cause unnecessary computation, and if the number of linguistic variables is chosen too small it will result in inaccuracy. According to experience and experimental results, four linguistic variables are suitable to represent the input domain and the output domain in this case. The Gaussian membership function is a commonly used membership function and it is applied to represent the different linguistic variables for input and output domains in this paper. Gaussian functions are realized by

$$\mu(x) = \exp\left(-\frac{(x-a)^2}{\sigma^2}\right) \tag{3}$$

where a is the center of the membership function and σ is the width of the membership function.

The center average defuzzification method is a commonly used defuzzification method in fuzzy theory [16]. In this paper the center average defuzzification method is used. The range of the input variable (absolute value of sensor voltage) is 0–6 V. If the overlap between different membership functions is too large, some values in the input domain may not have an effect on the output. If the overlap between different membership functions is too small, the corresponding linguistic variables will be difficult to differentiate. In order to cover the range of input variable with the proper overlap, the centers of the four membership functions for the input variable are defined averagely in the input range as 2, 3, 4, and 5 and the width of each input membership function is chosen as 0.541. In the center average defuzzification method, only the centers of the output membership functions affect the final output. The centers of the output membership functions are defined averagely in the output range as 0.4, 1.166, 1.8333, and 2.5. 0.4 is the minimum value of the output variable (PPF scalar gain). 2.5 is the maximum value of the output variable. The shapes of the resulting input membership functions and the output membership functions are shown in figures 7 and 8, respectively.

(3) *Determine the fuzzy inference rules.* The fuzzy inference is the core of the fuzzy logic method. By experience, the general strategy is that when the vibration amplitude is large a small PPF scalar gain is applied so as to suppress the initial overshoot; when the vibration amplitude is small a large PPF scalar gain is applied to achieve quick vibration suppression.

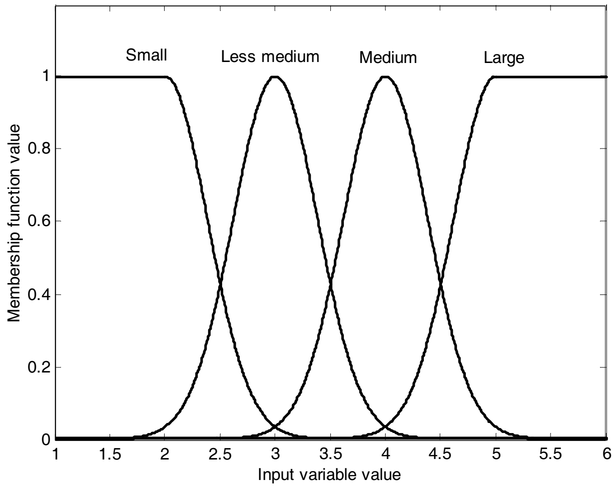

Figure 7. Diagram of the membership functions for the input variable.

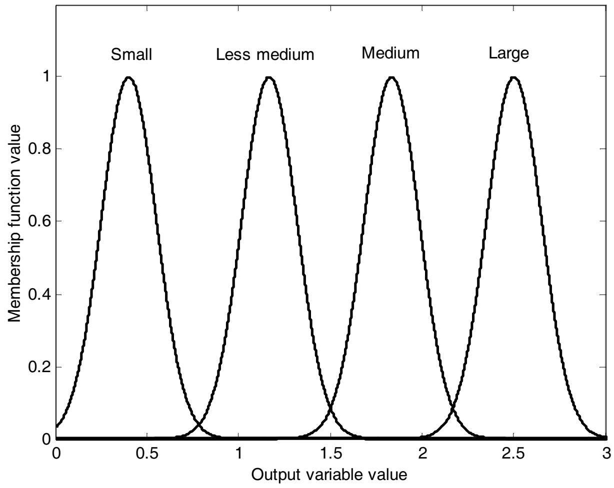

Figure 8. Diagram of the membership functions for the output variable.

The fuzzy inference rules are written below:

- if the vibration amplitude is small, then the PPF gain is large;
- if the vibration amplitude is less medium, then the PPF gain is medium;
- if the vibration amplitude is medium, then the PPF gain is less medium;
- if the vibration amplitude is large, then the PPF gain is small.

(4) *Defuzzification method.* The center average defuzzification method [16] is used. Let $\bar{y}^l$ be the center of the lth output membership function. The output y^* of the fuzzy gain tuner is

$$y^* = \frac{\sum_{l=1}^{4} \bar{y}^l \mu_l(x)}{\sum_{l=1}^{4} \mu_l(x)} \tag{4}$$

where $\mu_i(x)$ is the ith input membership function, and x is the input variable.

Figure 9 demonstrates the input–output data map for the fuzzy system with the membership function and the fuzzy inference rules defined above.

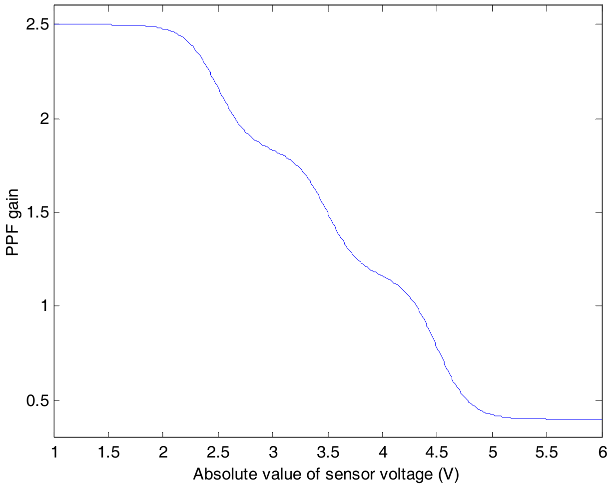

Figure 9. Input(absolute value of sensor signal)–output(gain) map of the fuzzy gain tuner.

4.2. Design procedure of gain tuner using batch least squares fuzzy method

The drawback of the design procedure using the traditional fuzzy method is that the parameters of the membership functions of the input variable and output variable and the fuzzy inference rules are decided subjectively. Therefore, the choice of the parameters of the fuzzy gain tuner is very important and there are very few ways to guide the design of the fuzzy gain tuner. The batch least squares method is used to train the fuzzy system with a given input–output data set. After being trained, the fuzzy system can behave in a desired way. In this paper, the desired training data are obtained experimentally based on experience and the batch least squares algorithm is used to train the centers of the output membership function of the fuzzy system. The fuzzy system to be trained has the same input membership functions and fuzzy inference rules as the traditional fuzzy system described in section 4.1.

(a) *The training data.* There are many different requirements in various aspects of the vibration control. In this experiment, the aim is to depress the initial overshoot caused by a PPF controller. Also, the vibration should be suppressed as soon as possible, preferably in less than 5 s.

The desired input–output training data are shown in figure 10. The peak value of the amplitude of each vibration cycle is taken as the input to the fuzzy gain tuner and the corresponding gain value is taken as the output from fuzzy gain tuner. The designed input (sensor voltage of the vibration amplitude)–output (PPF scalar gain) data map shown in figure 11 is used as training data to train the fuzzy system.

(b) *Batch least squares (BLS) algorithm.* The fuzzy system to be trained by the batch least squares algorithm is described by equation (5).

$$\begin{aligned} y_i &= \frac{\sum_{k=1}^{R} b_k \mu_k(x_i)}{\sum_{k=1}^{R} \mu_k(x_i)} \\ &= \frac{b_1 \mu_1(x_i)}{\sum_{k=1}^{R} \mu_k(x_i)} + \cdots + \frac{b_R \mu_R(x_i)}{\sum_{k=1}^{R} \mu_k(x_i)} \qquad (i = 1, \ldots, M) \end{aligned} \tag{5}$$

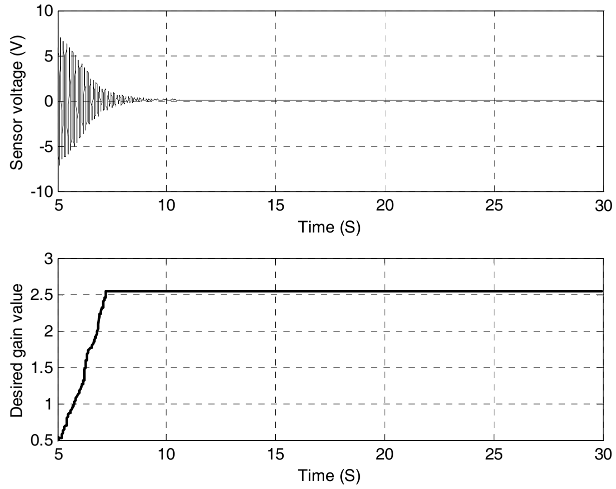

Figure 10. Desired input–output data (training data).

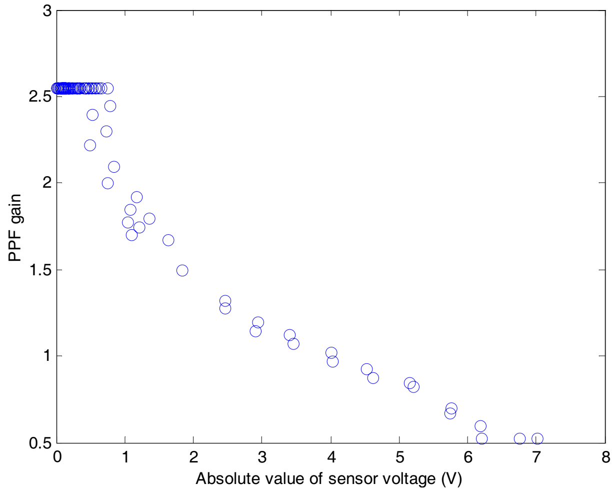

Figure 11. Desired input–output training data map.

where x_i is the ith input datum in the training data, y_i is the corresponding ith output datum in the training data, $\mu_k(x_i)$ is the input membership function value of the kth rule, b_i is the center value of the ith output membership function, and b_i, $i = 1, 2, \ldots, R$, values are the parameters to be identified. R is the number of fuzzy inference rules and M is the number of training data.

Define

$$\theta = [b_1, b_2 \ldots, b_R]^{\mathrm{T}} \tag{6}$$

and

$$X_i = \left[\frac{\mu_1(x_i)}{\sum_{k=1}^{R} \mu_k(x_i)}, \ldots, \frac{\mu_R(x_i)}{\sum_{k=1}^{R} \mu_k(x_i)} \right]^{\mathrm{T}}. \tag{7}$$

With equations (6) and (7), equation (5) can be expressed as

$$y_i = \theta^{\mathrm{T}} X_i. \tag{8}$$

Define

$$Y = [y_1, y_2, \ldots, y_M]^{\mathrm{T}} \tag{9}$$

and

$$\phi = [[X_1]^{\mathrm{T}} [X_2]^{\mathrm{T}} \cdots [X_M]^{\mathrm{T}}]^{\mathrm{T}}. \tag{10}$$

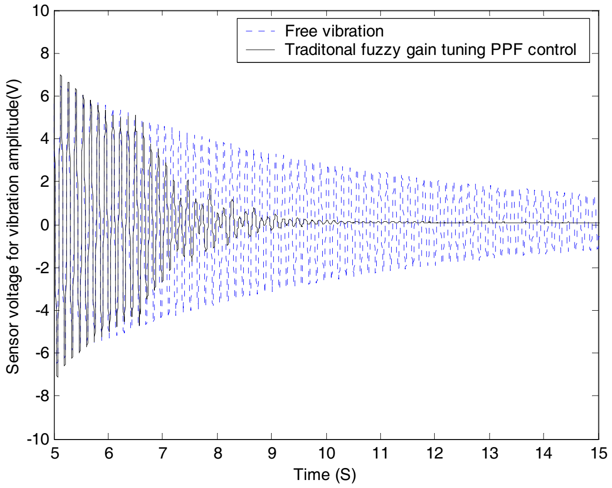

Figure 12. Comparison of the free vibration and the traditional fuzzy gain tuning PPF control.

Assume $\hat{\theta}$ as the estimate of θ. By using the definitions in equations (9) and (10), the error function for estimation is defined as

$$E = Y - \phi\hat{\theta}. \tag{11}$$

If $V(\hat{\theta}) = \frac{1}{2} E^{\mathrm{T}} E$ is defined as a measure of the accuracy of the approximation for a given $\hat{\theta}$, then

$$2V(\hat{\theta}) = E^{\mathrm{T}} E = Y^{\mathrm{T}} Y - Y^{\mathrm{T}} \phi\hat{\theta} - \hat{\theta}^{\mathrm{T}} \phi^{\mathrm{T}} Y + \hat{\theta}^{\mathrm{T}} \phi^{\mathrm{T}} \phi\hat{\theta}. \tag{12}$$

Assuming that $\phi^{\mathrm{T}}\phi$ is invertible, adding the term $Y^{\mathrm{T}}\phi(\phi^{\mathrm{T}}\phi)^{-1} \phi^{\mathrm{T}} Y - Y^{\mathrm{T}}\phi(\phi^{\mathrm{T}}\phi)^{-1}\phi^{\mathrm{T}} Y$ to the right side of equation (12) gives

$$\begin{aligned} 2V(\hat{\theta}) &= Y^{\mathrm{T}} Y - Y^{\mathrm{T}} \phi\hat{\theta} - \hat{\theta}^{\mathrm{T}} \phi^{\mathrm{T}} Y + \hat{\theta}^{\mathrm{T}} \phi^{\mathrm{T}} \phi\hat{\theta} \\ &\quad + Y^{\mathrm{T}}\phi(\phi^{\mathrm{T}}\phi)^{-1}\phi^{\mathrm{T}} Y - Y^{\mathrm{T}}\phi(\phi^{\mathrm{T}}\phi)^{-1}\phi^{\mathrm{T}} Y \\ &= Y^{\mathrm{T}}(I - \phi(\phi^{\mathrm{T}}\phi)^{-1}\phi^{\mathrm{T}})Y \\ &\quad + (\hat{\theta} - (\phi^{\mathrm{T}}\phi)^{-1}\phi^{\mathrm{T}} Y)^{\mathrm{T}} \phi^{\mathrm{T}}\phi(\hat{\theta} - (\phi^{\mathrm{T}}\phi)^{-1}\phi^{\mathrm{T}} Y). \end{aligned} \tag{13}$$

The first item in the right side of equation (13), $Y^{\mathrm{T}}(I - \phi(\phi^{\mathrm{T}}\phi)^{-1}\phi^{\mathrm{T}})Y$, is independent of θ. Therefore, $V(\hat{\theta})$ cannot be reduced via this term. To achieve the minimum value of $V(\hat{\theta})$, $\hat{\theta}$ is chosen to make the second term on the right side of equation (13) zero. That is,

$$\hat{\theta} = (\phi^{\mathrm{T}}\phi)^{-1}\phi^{\mathrm{T}} Y. \tag{14}$$

So, $V(\hat{\theta})$ achieves its minimum by the estimation given by equation (14). This is called the batch least squares algorithm [16].

In this experiment, the input–output data (figure 11) are used as the training data for the fuzzy system. The absolute value of sensor signal of the vibration amplitude is the input data x_i and the value of the PPF scalar gain is the output data y_i. After being trained by the desired input–output data map shown in figure 11 with the batch least squares algorithm, the estimation of the centers of the output membership functions is given as

$$\begin{aligned} \hat{\theta} &= [\hat{b}_1, \hat{b}_2, \ldots \hat{b}_R]^{\mathrm{T}} = [\hat{b}_1, \hat{b}_2, \hat{b}_3, \hat{b}_4] \\ &= [2.4640, 0.9233, 1.0968, 0.6627]. \end{aligned} \tag{15}$$

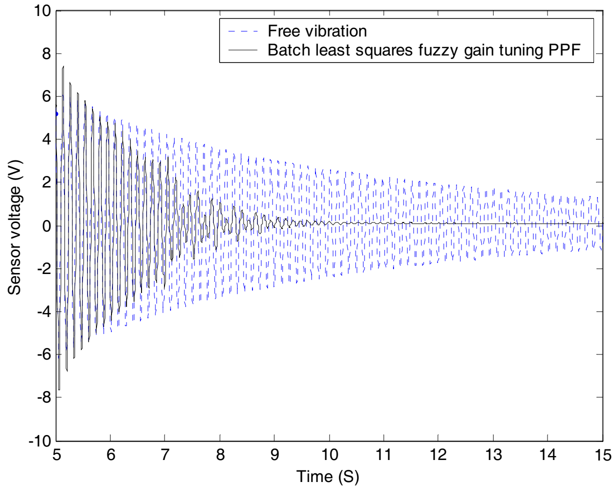

Figure 13. Comparison of free vibration and the batch least squares fuzzy gain tuning.

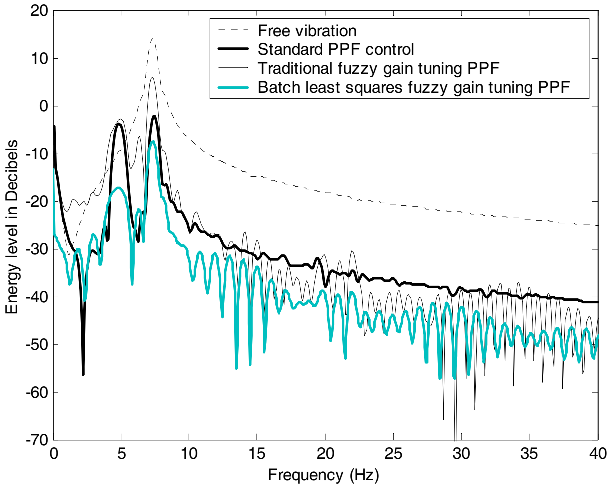

Figure 14. The PSD comparisons between 6 and 8 s.

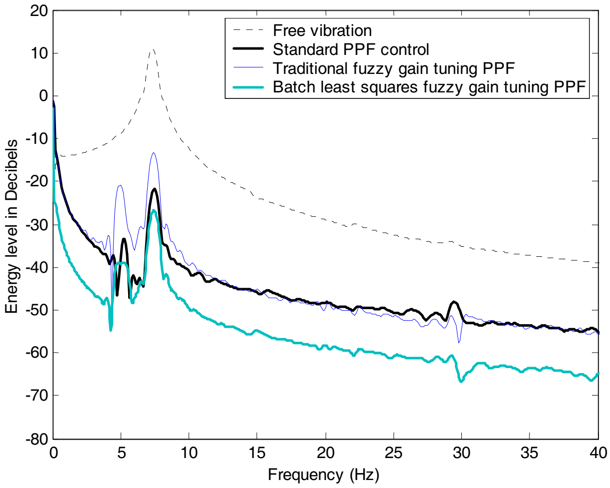

Figure 15. The PSD comparisons between 8 and 10 s.

5. Experimental results

In order to demonstrate the effectiveness of the PPF control with the BLS fuzzy gain tuner, tests are conducted using the experimental set-up and procedures described in section 2. Traditional fuzzy gain tuning PPF control and batch least squares fuzzy gain tuning PPF control will be implemented in this section. For comparison purposes, the results of free vibration (figure 4) and standard PPF control (figure 6) will be also used in this section.

5.1. Traditional fuzzy gain tuning PPF

The traditional fuzzy gain tuning method described in section 4.1 is implemented on the FRP I-beam. The comparison of the time responses of free vibration and the traditional fuzzy gain tuning is shown in figure 12. From the experimental result, the initial overshoot is suppressed, and the vibration is successfully depressed in 5 s. However, the vibration suppression performance during the 5–7 s period is not satisfactory.

5.2. Batch least squares fuzzy gain tuning PPF control

The batch least squares algorithm described in section 4.2 is implemented to train the fuzzy system to tune the PPF scalar gain. The comparison of the time responses of free vibration and PPF control with the batch least fuzzy gain tuning is shown in figure 13. From the experimental result, it can be seen that the batch least squares fuzzy gain tuning has suppressed the initial overshoot of the PPF control and also results in quick vibration suppression. Importantly, compared with the result of traditional fuzzy gain tuning, batch least squares fuzzy gain tuning has achieved a better result during the 5–7 s period. Batch least squares fuzzy gain tuning has achieved a satisfactory result.

Comparisons of the power spectral density (PSD) of the free vibration, control with standard PPF, control with traditional fuzzy gain tuning PPF and control with batch least squares fuzzy gain tuning PPF are demonstrated in figures 14 and 15. From the PSD comparison between 6 and 8 s (figure 14) and the PSD comparison between 8 and 10 s (figure 15), it can be concluded that the batch least squares fuzzy gain tuning PPF suppresses the vibration better than the standard PPF control and the traditional fuzzy gain tuning PPF control.

The comparison of the output of training data and the experimental output data of the batch least squares fuzzy gain tuner is shown in figure 16. It reveals that the experimental data closely match the desired data, which implies that the fuzzy gain tuner is trained successfully. The fuzzy system can also be trained for other requirements of vibration control, provided that the desired input–output map data sets are available.

5.3. Comparative study of experimental results

From the experimental results, we have the following observations and conclusions.

(1) The standard PPF control can effectively suppress the vibration with a large scalar gain. However, it is accompanied by initial overshoot.

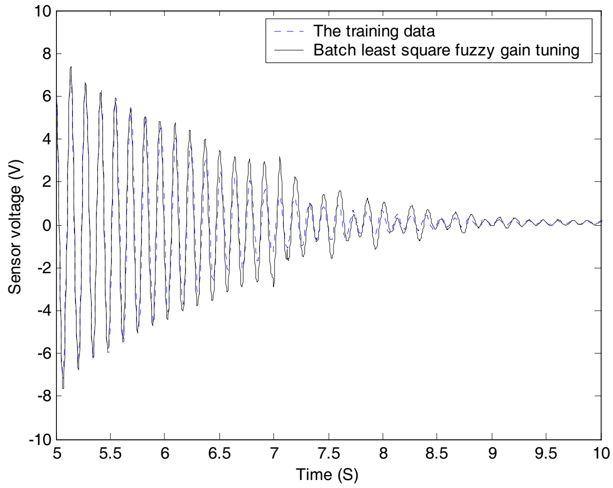

Figure 16. Comparison of the training data and the batch least squares fuzzy gain tuning.

(2) The traditional fuzzy system can be applied to tuning the scalar gain of a PPF control. However, due to the use of the trial-and-error method to determine the fuzzy system parameters it cannot guarantee a satisfactory overall result. In the experiment of PPF control with traditional fuzzy gain tuning there is no initial overshoot; however, the vibration suppression during the period from the fifth to seventh second is not effective.

(3) The batch least squares algorithm trains the fuzzy system with the desired data so that the fuzzy gain tuner can perform in the desired manner. The experimental data clearly demonstrate that the PPF control with batch least squares fuzzy gain tuning successfully suppresses the initial overshoot while maintaining quick vibration suppression and therefore is superior to both the standard PPF control and the PPF control with traditional fuzzy gain tuning.

6. Conclusion

The PPF control is an effective vibration suppression method; however, it is accompanied by initial overshoot when the PPF gain is large. Two improved approaches to suppress the initial overshoot are presented in this paper. One approach tunes the scalar gain of the PPF control by using the traditional fuzzy gain tuning while the other approach applies batch least squares fuzzy gain tuning. Both approaches yield good results, and the batch least squares PPF gain tuning is better for vibration suppression in the initial stage. Experimental results show that when the batch least squares fuzzy gain tuner is used the initial overshoot is eliminated while the vibration is quickly suppressed. The proposed method of PPF control with the batch least squares fuzzy gain tuner is superior to both the standard PPF control and the PPF control with traditional fuzzy gain tuning.

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